

New perspectives on the uncertainty principle

Yuval Wigderson (Stanford)
Joint with Avi Wigderson

March 26, 2021

Uncertainty: that is appropriate for
the matters of this world.

Joel and Ethan Coen
The Ballad of Buster Scruggs

Background

Heisenberg (1927): It is impossible to simultaneously determine a particle's position and momentum to arbitrary precision.

Kennard, Weyl (1927-8): Mathematical formalism:

$$\sigma_x \sigma_p \geq \frac{h}{4\pi}.$$

Also applies to any pair of **canonically conjugate** variables: quantities related by a **Fourier transform**.

From physics to math: relations to functional analysis, PDEs, microlocal analysis, wavelets, signal processing,...

The Fourier transform

Continuous

Given $f: \mathbb{R} \rightarrow \mathbb{C}$, we define

$$\hat{f}(\xi) = \int_{-\infty}^{\infty} f(x) e^{-2\pi i x \xi} dx.$$

We can recover f from \hat{f} as

$$f(x) = \int_{-\infty}^{\infty} \hat{f}(\xi) e^{2\pi i x \xi} d\xi.$$

Throughout, f is “nice enough”.
It suffices that $f, \hat{f} \in L^1$.

Discrete

For $f: \mathbb{Z}/N\mathbb{Z} \rightarrow \mathbb{C}$,

$$\hat{f}(\xi) = \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} f(x) e^{-2\pi i x \xi / N}$$

and we can recover

$$f(x) = \frac{1}{\sqrt{N}} \sum_{\xi=0}^{N-1} \hat{f}(\xi) e^{2\pi i x \xi / N}.$$

The uncertainty principle(s)

For $f: \mathbb{R} \rightarrow \mathbb{C}$

- If f has compact (finite-measure) support, then \hat{f} does not.
- Hardy: f and \hat{f} cannot both decay faster than e^{-x^2} .
- Heisenberg:

$$V(f)V(\hat{f}) \geq \frac{\|f\|_2^2 \|\hat{f}\|_2^2}{16\pi^2},$$

where $V(f) = \int_{\mathbb{R}} x^2 |f(x)|^2 dx$.

- Hirschman, Beckner:

$$H(f) + H(\hat{f}) \geq \log \frac{e}{2},$$

where $\|f\|_2 = 1$ and $H(f) = \int_{\mathbb{R}} |f(x)|^2 \log |f(x)|^2 dx$.

For $f: \mathbb{Z}/N\mathbb{Z} \rightarrow \mathbb{C}$

- Donoho-Stark:

$$|\text{supp}(f)| |\text{supp}(\hat{f})| \geq N.$$

- If $\|f|_S\|_2 \geq (1 - \varepsilon)\|f\|_2$ and $\|\hat{f}|_T\|_2 \geq (1 - \delta)\|\hat{f}\|_2$, then

$$|S||T| \geq N(1 - \varepsilon - \delta)^2.$$

- Biró, Meshulam, Tao: If N is prime,

$$|\text{supp}(f)| + |\text{supp}(\hat{f})| \geq N + 1.$$

- Dembo-Cover-Thomas:

$$H(f) + H(\hat{f}) \geq \log N,$$

where $\|f\|_2 = 1$ and $H(f) = \sum_{x=0}^{N-1} |f(x)|^2 \log |f(x)|^2$.

Outline of the talk

Introduction

Our new perspective on the uncertainty principle

Examples

Interlude: generality and extensions

More examples

Conclusion

The primary uncertainty principle

We can bound $\|\hat{f}\|_\infty$ by $\|f\|_1$: observe that for any $\xi \in \mathbb{R}$,

$$|\hat{f}(\xi)| = \left| \int_{-\infty}^{\infty} f(x)e^{-2\pi i x \xi} dx \right| \leq \int_{-\infty}^{\infty} |f(x)| |e^{-2\pi i x \xi}| dx = \|f\|_1$$

which implies that

$$\|\hat{f}\|_\infty = \sup_{\xi \in \mathbb{R}} |\hat{f}(\xi)| \leq \|f\|_1.$$

Similarly, $\|f\|_\infty \leq \|\hat{f}\|_1$. Multiplying these together, we find

$$\frac{\|f\|_1}{\|f\|_\infty} \cdot \frac{\|\hat{f}\|_1}{\|\hat{f}\|_\infty} \geq 1. \quad (*)$$

$\|f\|_1/\|f\|_\infty$ measures localization; this is **the** uncertainty principle!

How to derive other uncertainty principles

$$\frac{\|f\|_1}{\|f\|_\infty} \cdot \frac{\|\hat{f}\|_1}{\|\hat{f}\|_\infty} \geq 1 \quad (*)$$

Say we wish to prove an uncertainty principle

$$L(f) \cdot L(\hat{f}) \geq C$$

for some “measure of localization” L .

(*) contains all the “uncertainty”. It suffices to prove

$$L(g) \geq c \frac{\|g\|_1}{\|g\|_\infty} \quad \text{or} \quad L(g) \geq \left(\frac{\|g\|_1}{\|g\|_\infty} \right)^c \quad \text{or} \quad \dots$$

for any **single** function g . Then plug in $g = f, g = \hat{f}$.

Example 1: Support size

For any $g : \mathbb{R} \rightarrow \mathbb{C}$,

$$\begin{aligned}\|g\|_1 &= \int_{\mathbb{R}} |g(x)| \, dx \\ &= \int_{\text{supp}(g)} |g(x)| \, dx \\ &\leq |\text{supp}(g)| \|g\|_{\infty}\end{aligned}$$

where $|\cdot|$ is Lebesgue measure.

So

$$|\text{supp}(g)| \geq \frac{\|g\|_1}{\|g\|_{\infty}}.$$

Therefore

$$\begin{aligned}|\text{supp}(f)| |\text{supp}(\hat{f})| &\geq \frac{\|f\|_1}{\|f\|_{\infty}} \cdot \frac{\|\hat{f}\|_1}{\|\hat{f}\|_{\infty}} \\ &\geq 1.\end{aligned}$$

If $f : \mathbb{Z}/N\mathbb{Z} \rightarrow \mathbb{C}$, then

$$\|\hat{f}\|_{\infty} \leq \frac{1}{\sqrt{N}} \sum_{x=0}^{N-1} |f(x)| = \frac{\|f\|_1}{\sqrt{N}}.$$

So in the discrete setting,

$$\frac{\|f\|_1}{\|f\|_{\infty}} \cdot \frac{\|\hat{f}\|_1}{\|\hat{f}\|_{\infty}} \geq N.$$

Therefore, the same argument gives the Donoho–Stark UP:

For non-zero $f : \mathbb{Z}/N\mathbb{Z} \rightarrow \mathbb{C}$,

$$|\text{supp}(f)| \cdot |\text{supp}(\hat{f})| \geq N.$$

Example 2: Approximate support

Say that g is ε -supported on $E \subset \mathbb{R}$ if

$$\int_E |g(x)| dx \geq (1 - \varepsilon) \|g\|_1.$$

Theorem (Williams)

If $f: \mathbb{R} \rightarrow \mathbb{C}$ is ε -supported on S and \hat{f} is δ -supported on T , then

$$|S||T| \geq (1 - \varepsilon)(1 - \delta).$$

Proof.

If g is ε -supported on E , then

$$(1 - \varepsilon) \|g\|_1 \leq \int_E |g(x)| dx \leq |E| \|g\|_\infty \implies |E| \geq (1 - \varepsilon) \frac{\|g\|_1}{\|g\|_\infty}.$$

So

$$|S||T| \geq \left((1 - \varepsilon) \frac{\|f\|_1}{\|f\|_\infty} \right) \left((1 - \delta) \frac{\|\hat{f}\|_1}{\|\hat{f}\|_\infty} \right) \geq (1 - \varepsilon)(1 - \delta). \quad \square$$

How general is this?

All our results follow from the primary uncertainty principle

$$\frac{\|f\|_1}{\|f\|_\infty} \cdot \frac{\|\hat{f}\|_1}{\|\hat{f}\|_\infty} \geq 1, \quad (*)$$

as well as “universal” bounds that hold for a **single** function.

(*) only needed that $\|\hat{f}\|_\infty \leq \|f\|_1$, $\|f\|_\infty \leq \|\hat{f}\|_1$.

Theorem

Let A, B be a linear operators with

$$\|A\|_{1 \rightarrow \infty} \leq 1, \|B\|_{1 \rightarrow \infty} \leq 1, \text{ and } \|BAf\|_\infty \geq k\|f\|_\infty.$$

Then

$$\frac{\|f\|_1}{\|f\|_\infty} \cdot \frac{\|Af\|_1}{\|Af\|_\infty} \geq k.$$

We call such operators *k-Hadamard*. Examples from coding theory, block designs, quantum algebra, fractional Fourier transforms...

Example 3: Other norms

Theorem

For any $1 \leq p \leq \infty$ and any non-zero $f: \mathbb{R} \rightarrow \mathbb{C}$,

$$\frac{\|f\|_1}{\|f\|_p} \cdot \frac{\|\hat{f}\|_1}{\|\hat{f}\|_p} \geq 1.$$

Proof.

For any $g: \mathbb{R} \rightarrow \mathbb{C}$,

$$\|g\|_p^p = \int_{\mathbb{R}} |g(x)|^p dx \leq \|g\|_{\infty}^{p-1} \int_{\mathbb{R}} |g(x)| dx = \|g\|_{\infty}^{p-1} \|g\|_1.$$

So $\|g\|_1^{p-1} \|g\|_p \leq \|g\|_{\infty}^{p-1} \|g\|_1$. Therefore,

$$\frac{\|g\|_1}{\|g\|_p} \geq \left(\frac{\|g\|_1}{\|g\|_{\infty}} \right)^{\frac{p-1}{p}} \implies \frac{\|f\|_1}{\|f\|_p} \frac{\|\hat{f}\|_1}{\|\hat{f}\|_p} \geq \left(\frac{\|f\|_1}{\|f\|_{\infty}} \frac{\|\hat{f}\|_1}{\|\hat{f}\|_{\infty}} \right)^{\frac{p-1}{p}} \geq 1. \quad \square$$

Example 4: The Heisenberg uncertainty principle

$$V(f)V(\hat{f}) \geq C\|f\|_2^2\|\hat{f}\|_2^2, \text{ where } V(f) = \int_{\mathbb{R}} x^2|f(x)|^2 dx.$$

Here, we will use $\frac{\|f\|_1}{\|f\|_2} \frac{\|\hat{f}\|_1}{\|\hat{f}\|_2} \geq 1$ as a primary uncertainty principle.

So we want a lower bound on $V(g)$ in terms of $\|g\|_1/\|g\|_2$.

Lemma: $\frac{V(g)}{\|g\|_2^2} \geq c \left(\frac{\|g\|_1}{\|g\|_2} \right)^4$.

Proof sketch: Let $T = \frac{1}{8}(\|g\|_1/\|g\|_2)^2$, so that $\int_{-T}^T |g| \leq \frac{1}{2}\|g\|_1$. Then

$$\frac{1}{2}\|g\|_1 \leq \int_{|x|>T} \frac{x}{x} |g(x)| dx \leq \underbrace{\left(\int_{|x|>T} \frac{1}{x^2} dx \right)^{\frac{1}{2}}}_{\sqrt{2/T}} \underbrace{\left(\int_{\mathbb{R}} x^2 |g(x)|^2 dx \right)^{\frac{1}{2}}}_{\sqrt{V(g)}}.$$

Using the same ideas, we can prove uncertainty relations for other moments and norms of $|f|, |\hat{f}|$; similar to results of Cowling-Price.

The constant we get is not optimal. This is probably an unavoidable shortcoming of this technique.

Summary

- Many (but not all!) uncertainty principles follow from a simple and general framework.

$$\frac{\|f\|_1}{\|f\|_\infty} \cdot \frac{\|\hat{f}\|_1}{\|\hat{f}\|_\infty} \geq 1$$

- To prove other uncertainty principles, simply prove a bound that holds for any **single** function.
- Standard proofs of many of these results use special properties of the Fourier transform; we only use basic calculus facts.
- Shortcomings: rarely gets the correct constant, cannot prove all uncertainty principles. But these lead to interesting questions...
- The only property of the Fourier transform we used is that it and its inverse are bounded $L^1 \rightarrow L^\infty$. Thus, this works in much greater generality.

Other operators for which this works

The only property of the Fourier transform we used is that it and its inverse are bounded $L^1 \rightarrow L^\infty$. Thus, this works in much greater generality.

- Continuous case:

- ▶ Linear canonical transforms: given $M = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \in \text{SL}_2(\mathbb{R})$ with $b \neq 0$,

$$(L_M f)(\xi) = \frac{1}{\sqrt{|ib|}} \int_{-\infty}^{\infty} f(x) e^{i\pi(d\xi^2 - 2x\xi + ax^2)/b} dx.$$

- Discrete case:

- ▶ We can obtain uncertainty principles for many “structured” linear operators: Hadamard matrices, conference matrices, incidence matrices from discrete geometry, error-correcting codes...
- ▶ We can also get uncertainty principles for random matrices. The Fourier transform isn’t so special—almost all matrices satisfy uncertainty!

Further extensions and open problems

Theorem

Let A, B be linear operators with

$$\|A\|_{1 \rightarrow \infty} \leq 1, \|B\|_{1 \rightarrow \infty} \leq 1, \text{ and } \|BAf\|_{\infty} \geq k\|f\|_{\infty}.$$

Then

$$\frac{\|f\|_1}{\|f\|_{\infty}} \cdot \frac{\|Af\|_1}{\|Af\|_{\infty}} \geq k.$$

- Arbitrary pairs of norms – very useful for non-abelian groups.
- Multiple operators A_1, \dots, A_n – are there any applications?
- Do some non-linear operators have uncertainty principles?
- Can one prove the multidimensional Heisenberg uncertainty principle with these techniques? If $f: \mathbb{R}^n \rightarrow \mathbb{C}$, then

$$\left(\int_{\mathbb{R}^n} \|x\|_2^2 |f(x)|^2 dx \right) \left(\int_{\mathbb{R}^n} \|\xi\|_2^2 |\hat{f}(\xi)|^2 d\xi \right) \geq \frac{n^2}{16\pi^2} \|f\|_2^2 \|\hat{f}\|_2^2.$$

The main interest is getting the correct dependence on n .

Thank you!